EQUIPMENT PRICE FORECAST BASED ON T-S FUZZY NEURAL NETWORK

G.P. JIANG†, L. XIE†, and S.X. SUN†

†Department of Management Engineering and Equipment Economy, Naval Engineering University, Wuhan, China.
MonaMonroebs@yahoo.com

Abstract — As we all know, the factors affecting the price of equipment are more complicated, but these factors still have a great correlation. How can we accurately predict the price of equipment? Based on the study of the tight support and smoothness of wavelet function, this paper proposes a correlation variable weight wavelet neural network algorithm to predict the price of 162 devices. The test results show that if the weight is not reduced, the predicted price is 0, and the error is still large. However, by arranging the data from small to large, the variable weighted wavelet neural network algorithm is used to predict the result closer to the auction price, which overcomes the incompatibility of the algorithm iteration and provides a reference for accurately predicting the price of the device.

Keywords — T-S fuzzy neural network; equipment; price forecast.

I. INTRODUCTION
Equation pricing is a complex problem whose importance is considerable for research. Due to the large number of factors that affect equipment prices such as the large-scale data, many researchers will be plagued by its huge data. Because of its subjective one-sidedness and other factors, coupled with the lack of quantitative analysis, it is often impossible to determine both the best method to arrive at the most standard and the most appropriate price for the value of the equipment itself (Ying et al., 2015). It is well proved that only quantitative analysis can get more accurate results.

The result of the qualitative analysis research is relatively large, so now an over-quantification of qualitative change is required. Quantification itself is a process from ambiguity to clarity, which generally passes through several stages: decomposition to score to summary (Kuo et al., 2016). Based on this idea: The quantified objects are broken down into the necessary components in a reasonable way, and then each part is scored with reference to its own criteria. Then, the score of each part is multiplied by the weight and added. The resulting score is the quantified value of this object (Li, 2016).

II. STATE OF THE ART
Most foreign equipment pricing studies focus on the following three aspects, namely, the economic returns of equipment, the comparison of returns between both financial and equipment markets, and the correlation between both of them (Chakraborty et al. 2016). A network with both signal and weight blurred is much more complex than a network with only the blurred signal. So, fewer networks are implemented with this method (Li et al., 2017). Some scholars consider that the economic return of equipment is low.

From the early 1950s to the early 1960s, some scholars pointed out that the actual rate of return on paintings is only 0.55%, and there is still a large gap between the return rate of the bonds of the British government (Fujii et al., 2015). At that time, his article greatly influences on the research boom in the economic field of equipment (Anbalagan et al., 2015). In order to analyze some domestic factors affecting to product prices, some scholars have used the characteristic price model to investigate them. She believes that there are four main factors affecting the product, namely, the time of completion of the work, the time of sale, materials, and dimensions. In addition, some scholars have found that the instability of equipment prices is mainly due to supply locks.

Many analysis methods used by many researchers in China to explore equipment prices are based on qualitative analysis, and they are rarely quantified for analysis. A fuzzy neural network composed by multiple fuzzy inferences and weight distributors realizes multiple and multi-dimensional reasoning functions. Additionally, it simplifies the structure of the network by transforming the extensive connections of local networks into simple single connections.

Therefore, most of their research on equipment prices use estimation methods, such as the arithmetic evaluation price method, which means that the average transaction price of equipment sold is equal to that of a former scholar corresponding to the equipment, and the price of other equipment is calculated. The range of factors that affect the equipment price considered by this method is very narrow and not comprehensive, so the accuracy of the obtained results will be extremely low.

III. METHODOLOGY
A. T-S fuzzy neural network learning algorithm
The T-S fuzzy system has strong adaptability. It can constantly update the membership function of fuzzy subsets while updating automatically. The T-S fuzzy system defines the form of the "if-then" rule. In the case of the rule $R'$, there are the following fuzzy inferences:

$$R': x_i \text{ is } A_i',...,x_j \text{ is } A_j', \text{ then } y_k = p_{i1} x_i + p_{i2} x_j + ... + p_{iL} x_j$$  \hspace{1cm} (1)
Among them, the group is the fuzzy set of the fuzzy system; \( P_i \) (\( i=1,2,\ldots,k \)) is the fuzzy parameter; \( y_i \) is the output according to the fuzzy rule, the input part (i.e., the if part) is fuzzy, and the output part (i.e. the then part) is determined. Fuzzy inference means that the output is a linear combination of inputs. T-S fuzzy neural network is divided into four layers, namely input layer, fuzzy layer, fuzzy rule calculation layer, and output layer. The input layer is connected to the input vector \( x_1 \). The number of nodes is equal to the dimension of the input vector. The fuzzy membership value is obtained by the fuzzification layer using a membership function to fuzzify the input value, setting as \( \mu \).

The fuzzy multiplication formula is used to calculate the \( \alpha \) value, which is implemented on the fuzzy rule calculation layer. That formula is used to calculate the output value of the fuzzy neural network, which is implemented at the output layer. The first layer is the input layer, the number of nodes is the \( n \) value, and the input value is \( x = (x_1, x_2, \ldots x_n)^T \), setting
\[
m = 2 * n
\] (2)

The second layer is the obfuscation layer. This layer obfuscates the data from the input unit’s data. Each neuron implements the corresponding membership function \( \mu_{ji} \) \( i=1,2,\ldots,n; j=1,2,\ldots,m \). The \( m \) value is the total number of nodes of \( x \) in this layer. The Gaussian function is used to represent the form of the membership function as follows:
\[
\mu_{ji} = \exp(-(x-c_j)^2/(2*\sigma_j^2)) (i=1,2,\ldots,n; j=1,2,\ldots,m)
\] (3)

In equation (3), \( c_{ji} \) and \( \sigma_{ji} \) are the center and width of the membership function, respectively. The third layer is the fuzzy rule calculation layer. This layer is mainly used to match the antecedents of fuzzy rules, and the degree of applicability of each rule is calculated. That is, the fuzzy operator is used as the concatenation operator.
\[
a_i = \mu_{i1} * \mu_{i2} * \ldots * \mu_{in} \] (4)

In equation (4), \( i \in [1,2,\ldots,n] \), \( j \in [1,2,\ldots,m] \). the number of nodes in the fourth layer is the same as that of the third layer, which is achieved by normalization, which avoids the oscillation caused by the excessive correction parameters in the learning process. The formula for this layer is expressed as seen below:
\[
\tilde{a}_i = \frac{a_i}{\sum_{i=1}^{m} a_i}
\] (5)

In the back-piece network, the first layer is the input layer. This layer is mainly a constant item that gives fuzzy rules. The input value of the 0th node \( x_0 = 1 \). The second layer has \( m \) nodes. Its role is to calculate the post-condition of each rule:
\[
y_j = p_{j0} + p_{j1}x_1 + \ldots + p_{jn}x_n = \sum_{k=1}^{n} p_{jk}x_k
\] (6)

In equation (6), \( k=1,2,\ldots,n; j=1,2,\ldots,m \). The third layer completes the output calculation of the system:
\[
y = \sum_{j=1}^{m} \tilde{a}_j y_j
\] (7)

It can be seen that \( y \) is the weighted sum of the back pieces of each rule. The weighting coefficient is the degree of applicability after each fuzzy rule is normalized, that is, the connection weight of the third layer of the back piece is obtained from the output of the front piece network. The learning method of the fuzzy neural network and the learning method of the neural network are similar except for adjusting the parameters. The neural network adjustment parameters are the network connection rights and offsets, and are adjusted through learning. The fuzzy neural network adjustment is the membership function parameters, rules and other parameters. In neural networks or fuzzy neural networks, the training we often refer to is essentially a learning process. What is training? It is to enter a sample set (also called sample set or training set) into the network, and then adjust the parameters in the network according to certain rules (learning algorithm) to reduce the network output error. Error calculations. The structure of the fuzzy neural network established above is a locally approached forward feedback multiple-layer network, and the network learning training process can adopt the back-propagation (BP) algorithm. Since the fuzzy segmentation of each input component has been determined in the data analysis, the central value \( c_j \) and width \( b_j \) of the membership function of the second layer need to be corrected in learning. The performance indicators for learning are:
\[
e = y_d - y_c
\] (8)

In equation (8), \( y_d \) is the expected output of the network; \( y_c \) is the actual output of the network; \( e \) is the expected output and the actual output error.
\[
p_j/(k) = p_j/(k-1) - a_j \frac{\partial e}{\partial p_j}
\] (9)
\[
\frac{\partial e}{\partial p_j} = (y_d - y_c) a_j / \sum_{i=1}^{m} a_j x_i
\] (10)

In equations (9) and (10), \( p_j \) is the neural network coefficient; a is the network learning rate; \( x_i \) is the network input parameter; \( a_j \) is the input parameter membership degree product. Parameter correction:
\[
c_j/(k) = c_j/(k-1) - \beta \frac{\partial e}{\partial c_j}
\] (11)
\[
b_j/(k) = b_j/(k-1) - \beta \frac{\partial e}{\partial b_j}
\] (12)

In equations (11) and (12), \( c \) and \( b \) are the center and width of the membership function, respectively.

B. Transform-based Spline Interpolation Prediction

Algorithm for Weighted Value Sharing

Given \( n+1 \) d dimensional finite vector data \( V(x_i) = [x_{i1}, x_{i2}, \ldots, x_{id}] \) \( i=0,1,\ldots, n \) and
corresponding weights. The following gives the steps of transform-based weighted \( y_j (j = 0, 1, \ldots, n) \) spline interpolation prediction algorithm. First, get the correlation coefficient between each dimension data and weight

\[
    r_j = \frac{\text{cov}(x_j, y)}{\sqrt{D(x_j)D(y)}} \quad (j = 1, \ldots, d)
\]

\[
    x_j = [x_{0j}, x_{1j}, x_{2j}, \ldots, x_{nj}]^T,
\]

\[
    y_j = [y_0, y_1, \ldots, y_{nj}]^T.
\]

The \( \text{cov}(x_j, y) \) is the covariance and \( D(x_j), D(y) \) is the variance. The correlation coefficient is transformed as

\[
    w_j = a r_j + b \quad (j = 1, \ldots, d)
\]

To obtain the weight of each factor and normalized,

\[
    w_j = w_j / \sum_{j=1}^{d} w_j
\]

The calculation of the weighted values of each dimension of each factor \( y_j = w_j^* y \) \( (j = 1, \ldots, d) \), the score value matrix is obtained.

\[
    T_{(n+1) \times d}
\]

The natural spline interpolation function \( S(x_j) \) \( (j = 1, \ldots, d) \) is performed on \( x_j \) and \( y_j \) to obtain the transformation function relationship of the sharing weights of each fractal dimension. Predict the value of each dimension corresponding to the new vector data

\[
    V(x_{n+1}) = [x_{n+1,1}, x_{n+1,2}, \ldots, x_{n+1,d}]
\]

\[
    y_{n+1} = \sum_{j=1}^{d} S(x_{n+1,j})
\]

Error calculation of prediction weights:

\[
    (y_{n+1} - y_{n+1}^*) / y_{n+1}
\]

Contemporary equipment has become more and more popular in the contemporary market, but the price system in the equipment market is not perfect. This is due to the lack of a scientific and reasonable pricing mechanism in the market. Therefore, in order to avoid further deterioration of the phenomenon, we must develop a scientific and reasonable pricing method to make the equipment market on the right track.

**IV. RESULT ANALYSIS AND DISCUSSION**

A. Weight Calculation Results

The T-S model’s fuzzy neural network algorithm is used to study the five major factors affecting equipment prices, namely, age, modeling, decoration, size, and pattern. Through these factors, the equipment price is evaluated and tested. The specific process is as follows: Select the number of model parameters, and the number of equipment evaluation factors determines the number of neurons in the input layer of the fuzzy neural network. Because we have selected five equipment evaluation indicators of chronological, usage, decorative, size, and pattern factors, the number of input neurons is 5, and the number of linguistic variables for each input layer neuron is 2. Each Gaussian function contains two parameters, so the front piece network has a total of 20 parameters. Because there are five input neurons, the preceding net contains 20 parameters, and the back net contains one constant, so the back net has a total of 100 parameters (connection weights), so the total number of parameters is 120.

We select 12 samples of equipment at different time intervals and the weight of each indicator \( I_1, I_2, \ldots, I_{10} \) from the relevant data. The \( O_i \) is a value between 0 and 1, which is obtained by dividing the revenue of equipment in different periods by 10,000. The training sample consists of the first 11 sample data, and then uses the transformation-based weighted value-spline spline interpolation prediction algorithm to obtain the correlation coefficient between each dimension and the weight (Table 1). That is, transform \( w_j = 1.25^j \) to get the weight of each factor and normalize \( w = [0.1069, 0.1048, 0.0869, 0.1011, 0.1051, 0.1035, 0.1015, 0.0824, 0.1063] \).

The \( y_j = w_j^* y \) \( (j = 1, \ldots, d) \) is the formula for the weighted value sharing. This formula can obtain the weight matrix \( T_{(n+1) \times d} \) corresponding to the shared value matrix \( T_{(n+1) \times d} \). The data is shown in Fig. 1.

B. Product Price Forecast

Then we construct the fuzzy neural network by referring to the dimension of the training sample to determine the number of input and output nodes and the number of fuzzy membership functions of the fuzzy neural network. Because the input data is 5-dimensional and the output data is 1-dimensional, 5-1-1 is the structure of the fuzzy neural network, where 10 means there are 10 membership functions. Selecting 6 sets of coefficients P0-P5, the center c and width b of the fuzzy membership function can be arbitrarily obtained. Preparation of training samples. The original data set is normalized and the training data is normalized.
Figure 1. Correlation coefficient of every factors and income.

Table 1. The error detection of 59 samples results based on T-S fuzzy neural network.

<table>
<thead>
<tr>
<th>Art ceramic works</th>
<th>Age</th>
<th>Use</th>
<th>Decoration</th>
<th>Size</th>
<th>Pattern</th>
<th>Price</th>
<th>Predicted price and relative error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.015937</td>
<td>0.013144</td>
<td>0.006828</td>
<td>0.006220</td>
<td>0.0064457</td>
<td>0.0952</td>
<td>0.0990/-0.0403</td>
</tr>
<tr>
<td>2</td>
<td>0.0168749</td>
<td>0.01391726</td>
<td>0.0072303</td>
<td>0.014329</td>
<td>0.0068249</td>
<td>0.1008</td>
<td>0.0902/-0.1053</td>
</tr>
<tr>
<td>3</td>
<td>0.340306</td>
<td>0.0386591</td>
<td>0.0200841</td>
<td>0.016304</td>
<td>0.01895804</td>
<td>0.28</td>
<td>0.2798/-0.0006</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>72</td>
<td>0.1361224</td>
<td>0.18162236</td>
<td>0.2445849</td>
<td>0.159214</td>
<td>0.18958406</td>
<td>1.12</td>
<td>1.1156/0.0039</td>
</tr>
<tr>
<td>73</td>
<td>0.1361224</td>
<td>0.15463630</td>
<td>0.0803364</td>
<td>0.159810</td>
<td>0.22744875</td>
<td>1.12</td>
<td>1.1202/-0.0002</td>
</tr>
<tr>
<td>74</td>
<td>0.0853188</td>
<td>0.19070348</td>
<td>0.0843532</td>
<td>0.076838</td>
<td>0.079624</td>
<td>1.176</td>
<td>1.1706/0.0046</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>162</td>
<td>4.03129</td>
<td>2.97446</td>
<td>4.00561</td>
<td>4.7263</td>
<td>3.72496</td>
<td>18.3424</td>
<td>18.3047/0.0021</td>
</tr>
</tbody>
</table>

The mapminmax function is used to complete the normalization of the training data. The processed network input and output are within the [-1, 1] interval. The remaining 59 sets of data can be used to construct a neural network for prediction and verification.

The generalization of the network. Network training and testing. Here, 100 network trainings are...
selected, and the T-S fuzzy neural network model is used to obtain the prediction error of the test sample, as shown in Table 1. From the results obtained above, we can see that the error in the experimental results is large, and the main reason for the large error is due to the large weight of each factor. In order to make the weights smaller, the adjustment value of the network changes greatly, and the weights and prices of various factors are multiplied, as shown in the table. Here, the data is rearranged in descending order of the price, then the weighted wavelet neural network algorithm is used to obtain the predicted price as shown in the table, and the absolute error obtained is shown in the figure. The relative error also does not exceed 0.04.

V. CONCLUSIONS
This paper provides quantitative research and analysis on equipment price forecast through the data of different factors that affect it. We have selected three kinds of superior approximation algorithms for price prediction and error analysis. The equipment prices are very different, and some similar equipment prices are a few hundred times different. Because the equipment has more complicated factors, but these still have a lot of relevance, how to predict the price of these equipment? In this paper, based on the study of tight support and smoothness of wavelet functions, an association variable weight wavelet neural network algorithm is proposed to predict the price of 162 equipment. The test results can be seen that if the weights are not reduced, the predicted prices are all 0, so the error is still very large. However, by arranging the data according to the arrangement of the data from small to large and using variable weighted wavelet neural network algorithm, the predicted results are closer to the auction price, which overcomes the inadaptability caused by the algorithm iteration. Therefore, when using this algorithm, we must pay attention to the similarity of the data, especially for a large amount, we must first sort the data. In this way, the weighted wavelet neural network algorithm predicts the result is more accurate, and has better generalization.

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